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**MOVING FORWARD:
THE ROLE OF MARKETING IN FOSTERING PUBLIC TRANSPORT USAGE**

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**MOVING FORWARD:
THE ROLE OF MARKETING IN FOSTERING PUBLIC TRANSPORT USAGE**

ABSTRACT

Public policy makers frequently aim to increase the use of public transport to reduce traffic congestion, pollution etc. This study therefore investigates the impact of firm-initiated marketing actions and traveler satisfaction on monthly cumulative travelled distance of a Western European railway firm, as well as possible effects of this cumulative travelled distance on satisfaction. Analysis of time-series data on travelled distance, advertising, promotions and satisfaction using a VARX model which accounts for seasonality, trending behavior and gasoline prices reveals positive effects of advertising and promotions. Advertising elasticities are considerably smaller than meta-analytic values of brand-advertising elasticities. Similarly, promotion elasticities are lower than those frequently reported in marketing. No effect of satisfaction on traveled distance is found. However, a negative effect of traveled distance on satisfaction is found, which could be explained by capacity constraints. The authors conclude that firm-initiated marketing actions are useful and effective in fostering public transport usage.

Keywords

Marketing, Advertising, Promotions, Satisfaction, Public Transport, Services

MOVING FORWARD: THE ROLE OF MARKETING IN FOSTERING PUBLIC TRANSPORT USAGE

1. INTRODUCTION

Multiple government policies aim at increasing the use of public transport. Increased public transport use can reduce congestion, parking problems, and decrease environmental pollution (i.e., smog, CO₂ emission, noise, etc.) (UITP 2013). In multiple countries public transport is to some extent liberalized and public transport firms have their own targets that may include the increase in the use of their public transport mode. For example, railway firms may aim to increase the miles traveled per year. In a more long-term multiple-year perspective they therefore may invest huge amounts in new and/or faster connections (i.e. faster trains). However, to achieve more short-term year-to-year growth objectives, other instruments need to be used. Specifically, these firms may use firm-initiated marketing actions and specifically advertising and promotions to attract more customers. Furthermore, they may invest in improving the delivered service quality, thus improving customer satisfaction and the attractiveness of the public transport (Gijzenberg, van Heerde, and Verhoef. 2015; Mouwen 2015), and ultimately fostering retention and repeated usage. While both types of investments may increase (repeated) public transport usage, they also come at a cost, thus affecting returns in two ways (see e.g., Rust, Lemon, and Zeithaml 2004). As a consequence, not just the understanding but even more so the quantification of the effects of these investments on public transport usage becomes of central importance to both public transport firms and public policy makers.

The choice for public transport options has gained much attention within transportation science. Within that literature, a large number of studies focusses on a) modeling these choices using logit-type of models (e.g. Greene 2003; Hensher 1994; Louviere 1988; Louviere and Hensher 1982), and b) uncovering the drivers of these choices (e.g. Arbues et al. 2015; Beirão and Cabral 2007; Friman and Gärling 2001; Hensher et al. 2013; Jakobsson Bergstad et al 2011; Mokhtarian and Salomon 2001). Surprisingly,

attention for customer satisfaction as a customer feedback metric that may drive repeated public transport usage is relatively scarce and in the case of firm-initiated marketing actions attention is even almost absent. Only one study considers the effects of service performance and specifically service crises on customer satisfaction for a railway firm (Gijzenberg, van Heerde, and Verhoef 2015), but this study does not consider the choice/sales consequences of customer satisfaction changes. Interestingly, while advertising is widely assumed to positively affect public transport usage, knowledge on the actual presence and strength of such effects is absent.

In contrast with the literature on transportation choices, marketing science has devoted substantial attention to the effects of advertising, promotions and customer satisfaction on performance outcomes. Researchers have discussed how advertising works (Vakratsas and Ambler 1999), and have assessed short- and long-term effects of advertising on sales (e.g. Sethuraman, Tellis, and Briesch 2011; Tellis 1998). Similarly, the effects of promotions have been studied extensively (Neslin and van Heerde 2009), and generally only short-term effects of promotions on brand sales are found. Most of the studies on the effects of advertising and promotions, however, are executed in a consumer packaged goods setting (e.g., Nijs et al. 2001; van Heerde et al. 2013). A recent meta-analysis by Sethuraman and colleagues (2011) clearly shows that, in general, services and certainly transportation services are neglected. As a consequence, meta-analytic findings are not necessarily representative for and applicable to transportation services. The effect of satisfaction on firm performance, on the other hand, has been studied in more sectors. Using the American Customer Satisfaction Index data (Fornell et al. 1996; Fornell, Rust, and Dekimpe 2010), researchers have considered the effects of customer satisfaction on multiple firm performance metrics, including sales and market share. The effects of customer satisfaction on these latter metrics are, however, not straightforward as sales growth may create service delivery problems, due to for example capacity problems (e.g. Anderson, Fornell, and Lehmann 1994; Rego, Morgan, and Fornell 2013). Studies specifically considering the effects of satisfaction on public transportation usage are, however, limited. We could only find a single study relating customer satisfaction about a railway firm to a customer's share of wallet in a B2B context (van Doorn and Verhoef 2008). Customer satisfaction, as a

consumer feedback metric (e.g. De Haan, Verhoef, and Wiesel 2015), in turn, could also be affected by firm-initiated marketing actions as it is based upon a post-hoc comparison between expected and perceived service performance, with for example the former possibly being influenced by advertising (see e.g. Zeithaml, Berry, and Parasuraman 1993). Hence, when studying the effects of advertising, promotions and customer satisfaction on sales, one should also consider the impact of advertising and promotions on customer satisfaction and their subsequent simultaneous effects on sales.

Addressing these gaps in both the transportation and marketing literature and in line with the call by Anderson et al. (2013) for more research with impact on societal well-being, the main research objective of this study is to assess whether and to what extent investing in firm-initiated marketing actions (advertising and promotions) and improved customer satisfaction can foster more (repeated) use (increased sales) of a public transport service. Acknowledging that investments can have both short- and long-term effects (e.g., Dekimpe and Hanssens 1995), our main empirical research questions are the following:

- 1) What are the short- and long-term effects of advertising and promotions on the sales of a public transport firm?
- 2) What are the short- and long-term effects of customer satisfaction on the sales of a public transport firm?

However, we do not limit ourselves to these two main questions but also investigate if and how advertising and promotions affect customer satisfaction of a public transport firm. A high delivered quality in public transport is important from a societal perspective and thus governments may use customer satisfaction measures as a key performance indicator for public transport firms (Gijzenberg, van Heerde, and Verhoef 2015)¹, and could even apply quality or satisfaction-based incentive payment systems (e.g. Hensher and Houghton 2004). Hence, it is interesting to explore potential relationships between firm-initiated marketing efforts and customer satisfaction. In addition, as public transport is characterized by a

¹ Gijzenberg and colleagues (2015) indicate in their paper that their concept of Perceived Service Quality can also be interpreted as an indicator of satisfaction.

rather fixed capacity inducing that strong increases in sales may reduce customer satisfaction due to capacity problems (i.e. limited number of seats in a train), we also explore effects of past sales on customer satisfaction,. Finally, as sales in our data can be divided into pass sales (subscription based) and individual-trip “free” tickets, we explore whether the marketing effects on sales differ between these two sales types, and whether these two types of sales affect each other (i.e. buying free tickets could induce future subscriptions).

To provide insights on these issues, we analyze a unique longitudinal dataset of a major European railway firm, for which we observe the monthly sales, advertising and promotion efforts, and customer satisfaction scores. Insights on the different short- and long-term elasticities are obtained by means of a Vector Autoregressive (VAR) model. Our results show positive effects of both advertising and promotions. No effects of satisfaction are found, while indeed we observe negative effects of sales on customer satisfaction.

2. CONCEPTUAL BACKGROUND

2.1. Public Transport Market

Public transport markets differ strongly from many other markets. In Europe, public transport markets have been liberalized (Pham 2013). However, the liberalization of public transport, and specifically trains, has been implemented in different degrees in the European Union. Whereas in some countries there is still a single state-owned monopolist that operates all railway connections (i.e. SNCF in France), in other countries public transport has been more liberalized. Such is for instance the case for the Netherlands where several firms operate trains on specific connections, while there is still a privatized major railway firm – with the state as the only shareholder – operating on the majority of the railway lines. The UK is probably the most liberalized country for public transports with no less than 28 public transport firms running trains. The UK situation, however, is really an exception (Pham 2013) and in general one could argue that public transport and specifically railway firms function in monopolistic (local) markets,

where direct competition with other railway operators is lacking (see also Mouwen 2015). For example, in our study context the public transport firm operates on all major train connections as well as on the majority of the other (regional) connections, both on which no other competitors operate. The competing firms are mainly active on specific regional connections, where they do not face other competitors operating. This situation contrasts strongly with the majority of markets being studied on the effects of advertising and promotions, in which typically brands compete with other brands. As a consequence, competition thus does not occur at the brand level, but at the category – or transport mode – level. Railway firms compete with other transport alternatives, such as cars, busses and in some cases even airplanes. The fast train connections between Amsterdam and Paris, for instance, compete with airline connections between these two cities. Studies in public transport have therefore mainly considered consumers' transport choices in which consumers had to state or reveal their preferences for specific transport alternatives (e.g., Hensher and Greene 2002; Hensher, Rose, and Greene 2005). In these models, marketing variables such as advertising are usually not included as predictors of transport choice. Researchers mainly used travel and transport mode attributes such as travel time and price as independent variables explaining these choices.

2.2. Demand Effects of Firm-Initiated Marketing Actions and Customer Satisfaction

Advertising can reach masses of geographically dispersed buyers at a low cost per exposure, through mass-media such as television, radio and print. Promotions include a wide assortment of temporary tools (i.e. discounts, premiums, coupons), which offer strong incentives to purchase as they invite and reward a quick response (Kotler and Armstrong 2014). Meta-analyses in marketing have summarized several decades of research on marketing mix effectiveness and have reported meta-analytic average advertising and promotion elasticities. As noted, this research has mainly been executed in markets for consumer packaged goods, although some studies have also considered services. Sethuraman, Tellis and Briesch (2011) report an average short-term advertising elasticity of .12, indicating that a 1% increase in the advertising budget results in a .12% immediate increase in sales. Long-term effects were

shown to be about twice as strong, with the reported long-term advertising elasticity equaling .24. The authors could not find significant different elasticities for services compared to goods, which is in our context an important result as public transport is a service. The effects of promotions have predominantly been studied in product markets. Short-term promotion effects on the sales of consumer packaged goods are generally much stronger in an absolute sense, with short-term elasticities of -3.63 (Bijmolt, van Heerde, and Pieters 2005), while long-term promotion elasticities are generally very weak or absent (e.g., Nijs et al. 2001). While insightful, the studies mentioned here are mainly based upon the analysis of consumer packaged goods, with some also including some services industries, but none of them including public transport. The studies also show a great dispersion of effect strength across different industries. As a consequence, the reported meta-analytic results are not necessarily representative for the situation in public transport and effect strength could be vastly different. Besides these meta-analytic studies which summarize the insights on advertising and promotion effectiveness, a large number of studies consider the impact of satisfaction on the financial performance of firms (see e.g. Gupta and Zeithaml 2006). In general, the idea is that satisfaction works as a customer feedback metric that increases firm performance (see e.g. De Haan, Verhoef, and Wiesel 2015; Hogueve et al. 2017), but meta-analytic average satisfaction elasticities and specific effects on sales are lacking.

The above reported meta-analytic results, in addition, are relevant only for the brand level; product level elasticities have been studied to a lesser extent in most recent marketing studies. In the public transport context, marketing should increase primary demand (Schultz and Wittink 1979). By doing so they should attract customers from other product (transport mode) categories functioning as alternatives for the studied public transport. When studying marketing mix effects one frequently distinguishes between such primary demand and secondary demand effects. Primary demand concerns the category level demand (category sales) (i.e. demand for toothpaste or public transport), while secondary demand concerns the demand at the brand level (brand sales) (i.e. demand for Crest (toothpaste) brand, or sales for Deutsche Bahn). While advertising is known to have some primary demand effects, the secondary demand effects are generally much stronger (e.g., Leone 1983). Leeflang and Reuijl (1985) report primary

demand effects in the cigarette market, but also report that this effect diminishes over time as markets become more mature. Similar findings have been reported for promotions. Bell, Chiang, and Padmanabhan (1999) suggest that 25% of the promotion elasticity can be attributed to primary demand effects, while the remaining 75% are secondary demand effects. Nijs et al. (2001) report that promotions have a short-term effect on primary (category) demand, but that long-term effects are generally absent. Thus, promotions may attract consumers to the category and increase the purchase volume of (existing) users, but it is unlikely that the sales boost will be permanent.

To the best of our knowledge there is no strong evidence for primary demand effects of satisfaction and other attitudes. Prior research suggests that satisfaction should increase customer retention and service usage (e.g., Bolton 1998; Bolton and Lemon 1999). While retention will not improve primary demand, service usage increases can, as the average usage per customer will increase. Research on satisfaction has shed some light on secondary demand effects by considering the relationship between satisfaction and market share. Empirical results here are mixed and even suggest negative relationships (Anderson, Fornell, and Lehmann 1994; Rego, Morgan, and Fornell 2013). These negative relationships may occur for multiple reasons. First, larger brands may find it more difficult to fully satisfy their large customers groups, while smaller (niche) brand can more easily satisfy their served customers with their more distinct offerings. Second, larger brands may face difficulties in managing satisfaction and service quality due to a larger complexity. Third, increases in market share and sales may lead to problems specifically in service contexts, as capacity constraints may induce lower satisfaction levels (i.e. longer waiting times for service desk). Fourth, higher customer satisfaction will not lead to increased share-of-wallet among customers, if the resulting satisfaction is not growing more than the customer's satisfaction with competing offers (e.g. Keiningham et al. 2014).

-- Insert Figure 1 about here --

We summarize our conceptual reasoning in Figure 1. Overall, existing research in marketing suggests that the effects of advertising and promotions on primary demand (for public transport) should be relatively low compared with most frequently reported secondary (brand) demand effects, and could even

not be present at all. Beyond that, the effect of customer satisfaction on primary demand is unclear and could even be negative.

2.3. Effects of Firm-Initiated Marketing Actions and Customer Satisfaction in Public Transport

The above discussion mainly takes a general demand perspective, but could a case be made that demand effects in public transport are different? Firm-initiated marketing actions can potentially attract more travelers. First, advertising may create more awareness, a stronger attitude and a resulting stronger preference for public transport. Second, promotions – being mainly temporary price reductions – may create more temporary demand, as the price is reduced. However, as noted, consumers have to choose between different travel alternatives. Some of these choices can be rather ad hoc (i.e. how to travel to a city for a museum visit), while others have long-term consequences, specifically when it involves investments in transport modes. For example, when consumers purchased a car for their daily travels (i.e. commuting), they are less inclined to switch to another alternative. An explanation for this could be that for consumers already having a car, the relative (generalized) cost of using a car for their next trip to work (or any place) is more likely to be below that of other modes than for those not owning a car (as the latter still would have to for instance rent a car). Similarly, when customers purchased a subscription for public transport, they will be less likely to switch to non-public transport alternatives. In sum, there are strong switching costs for many consumers, which makes it unlikely that consumers will easily switch between transport alternatives, at least in the short run (Klemperer 1995). In the longer run, these switches could be more likely, as subscription contracts end, cars can be sold etc. Due to these high short-term switching costs, sales effects of firm-initiated marketing efforts could be even lower. These observations are to some extent confirmed in a meta-analysis on price-elasticities of public transport demand (Holmgren 2007). In this meta-analysis, an average price elasticity of -0.38 is found, which is in line with the much often quoted price elasticity of -0.3 (e.g. Bresson et al. 2003; Webster and Bly 1980) but which is much lower than the average price elasticity found in marketing of -2.65 (Bijmolt, van Heerde, and Pieters 2005). Holmgren (2007) does, however, report stronger long-term price elasticities than short-term elasticities,

which is in line with our discussion that adjustments of consumer travel behavior takes some time. In sum, it is our contention that effects of advertising and promotions on primary demand for a public transport alternatives are likely to be lower than in other industries.

In general, one might assume that higher satisfaction increases sales, as consumers become more loyal (more repeat sales) and promote public transport to other consumers (word-of-mouth) (Gupta and Zeithaml 2006). However, public transport could also suffer from a similar potential negative relationship between satisfaction and sales as we observed for other services (Anderson, Fornell, and Lehmann 1994; Mouwen 2015). Public transport firms will have strong capacity constraints, as the available capacity (i.e. trains) is rather fixed and acquiring new capacity takes time (i.e. years). For example, currently demand for trains in the Netherlands is increasing, while capacity is not up to par to meet this increasing demand. Over the past couple of years, the Dutch National Railways have ordered new trains, but these will only become available in the coming years.

2.4. Firm-Initiated Marketing Actions - Satisfaction Effects

So far we mainly discussed the effects of firm-initiated marketing actions and customer satisfaction on sales. However, firm-initiated marketing efforts may also affect attitudes and, in our study, satisfaction. Satisfaction can be considered to be the outcome of a post-hoc comparison between expected and perceived service performance, hence formed after the actual service experience. This implies that service performance measures are important drivers of satisfaction (e.g., Gijsenberg, van Heerde, and Verhoef 2015). When expectations go up as a consequence of firm-initiated marketing actions like advertising (e.g. Zeithaml, Berry, and Parasuraman 1993), similar levels of actual delivered performance will likely result in more negative expectancy disconfirmation. This, in turn, implies more disappointed customers, and consequently a negative effect of advertising on satisfaction. Advertising, on the other hand, may also build stronger brands which receive more positive evaluations of similar actual service performance (e.g. Keller 1993), thus having a positive effect on satisfaction through higher perceived

service performance. We will explore the effects of advertising and promotions on customer satisfaction in our context having no strong prior expectations.

3. DATA AND PRELIMINARY INSIGHTS

3.1. Empirical Context

To provide insights on the answers raised above, we have access to a unique dataset provided by a major European railway firm that wishes to remain anonymous. The dataset is composed of monthly data on public transport usage, travelers' satisfaction and firm-initiated marketing actions, and covers nearly three years, starting April 2007, up to October 2009. Note that the studied firm operates the major train lines within the studied country, as well as the majority of smaller lines. We use the aggregated sales data for all the operated train connections excluding international connections. Hence, we do not study one specific train connection. The firm changes the price per traveled kilometer once per year (1st of January). Hence, there is very limited price variation in the data. Price variation may occur due to the use of some temporary price discounts, which we capture in our promotion variable. However, the relative price of public transport may change due to changes in gasoline prices. We therefore augment this dataset with data on the gasoline price evolution in the same period, thus adding information on the most obvious alternative transport mode, i.e. automobiles.

3.2. Public Transport Usage and Customer Satisfaction

Public transport usage is defined by two measures. The first measure covers, on a monthly basis, the total cumulative distance travelled by customers using single or round-trip one-time tickets (*ticket-dist*). It thus mainly covers occasional and irregular ad-hoc traveling, and accounts for 52% of the total distance travelled. The second measure covers, on a monthly basis, the total cumulative distance travelled by customers using multiple-trip month or year passes (*pass-dist*). It hence can be regarded as a measure that covers regular and repeated traveling, and accounts for 21% of the total distance travelled. As such,

these two measures reflect different travel motives. Whereas the second measure will mainly be driven by commuting (fixed-trajectory home-work journeys), the first measure is likely to depend more on leisure and other occasional motives. Such occasional and leisure traveling could, in addition, be hypothesized to be a first step in a stepping-stone sequence of convincing people to also use public transport on a daily basis for commuting. The remaining distance travelled is to the largest part covered by a special student travel card (25% of the remaining 27%). Given the specific nature of this card and its users which often have less access to alternative modes of transport like cars, we do not include this type of traveling in our analyses.

Customer satisfaction (*satis*) was measured through the following survey question: “*What is your general opinion/judgment about traveling per train?*” The respondents could answer this question on a 10 point scale (10 = excellent, 9 = very good, 8 = good, 7 = more than sufficient/satisfactory, 6 = sufficient/satisfactory, 5 = inadequate, 4 = very inadequate, 3 = bad, 2 = very bad, 1 = could not be worse). This survey question has been used by the railway firm for years to measure customer satisfaction (cfr. Gijzenberg, van Heerde, and Verhoef 2015). In the past, customer satisfaction has frequently been measured with multi-item scales (e.g., Tsiros and Mittal 2000). Nevertheless, although this might not be the perfect measure for customer satisfaction, when using available firm data, prior studies have also used single items, which are commonly used in practice to reduce survey length (e.g. Bolton 1998; van Doorn and Verhoef 2008. Satisfaction measurement is based on repeated cross-sections (e.g., Dekimpe et al. 1998; Fornell, Rust, and Dekimpe 2010; Srinivasan, Vanhuele, and Pauwels 2010). On a monthly basis, a representative sample of over 6000 customers is surveyed while riding on the train, covering the totality of the national network. Interviewers thereby apply quota sampling, thus making sure that the sample reflects the actual composition of the overall traveler/customer base. Once the target number for a certain segment of travelers is reached, no additional travelers from that segments are surveyed in that month. In addition, interviewers strive for an optimal distribution of surveyed travelers in each customer segment over the month, thus making sure that ratings are not based on the idiosyncrasies of for example one specific week

with bad weather during that month. The resulting national average satisfaction rating with the operational service performance across this sample is the satisfaction score for that month.

-- Insert Figure 2 about here --

Figure 2 shows the evolution of both public transport usage measures and customer satisfaction² over time. The full black line depicts the cumulative distance travelled with passes, and the dashed black line represents the cumulative distance travelled with tickets. The full grey line shows the evolution in customer satisfaction. Correlations between satisfaction and pass-dist on the one hand, and ticket-dist and pass-dist on the other hand are small and insignificant (.005 and -.067, respectively). However, stronger satisfaction is associated with more ticket-dist, with the correlation between both series equaling .403.

3.3. Firm-Initiated Marketing Actions

The firm uses two major types of firm-initiated marketing mix actions to foster public transport usage: advertising and promotional actions. Advertising (*adv*) is defined in monetary terms, the amount of euros spent on advertising campaigns in each month. Promotional actions can be classified into two categories: retailer promotions (*retpromo*) and own promotions (*ownpromo*). Retailer promotions are mainly targeting leisure travelers, offering them discounts on single or round-trip tickets or special day-trip packages. As such, these promotions only cover ticket-based travel. Own promotions are targeted at pass holders, and consist of special deals, discounts or other additional offerings. These promotions hence cover both offerings on ticket-based travel and on pass-based travel.

-- Insert Figure 3 about here --

Figure 3 shows the evolution of public transport usage and firm-initiated marketing actions. As in figure 2, the full black line depicts the cumulative distance travelled with passes, and the dashed black line represents the cumulative distance travelled with tickets. Light grey bars indicate months with retailer

² The customer satisfaction measure is a backward looking feedback measure which is only released at the beginning of the next month. To align its measurement with the actual period covered, we use the satisfaction reported in the current month as measure of satisfaction in previous month.

promotions, whereas dark grey bars indicate months with own promotions. The dotted line represents advertising expenditures. Correlations between advertising and both usage measures are small and insignificant (.136 for pass-dist and .047 for ticket-dist, respectively). A two-way anova with interaction showed significant positive main effects of both retailer ($p < .01$) and own promotions ($p < .01$) on ticket-dist, but no significant interaction effect ($p = .212$). As such, there are indications of a positive relation between the two types of promotions and occasional public transport usage, but effects are independent of each other. However, for pass-dist, no significant relations could be found when not accounting for other influencing factors.

4. METHODOLOGY

To analyze the data presented in previous section, we proceed in four steps. We first define the adstock variable which allows us to trace the cumulative effects of advertising actions. We then investigate the stationarity of the different time series. Subsequently, we formulate a flexible model to capture the marketing mix action effects and any feedback, carry-over and spill-over effects between the different types of traveling. We discuss the estimation procedure and then show how we determine both short-term and long-term effects. In our analyses, we log-transform the data series as this allows us to interpret the effects as elasticities. Such log-log functional form models, in addition, have shown to be very effective in capturing decreasing returns to marketing mix investments (see e.g. Hanssens, Parsons, and Schultz 2001, p. 102, or Leeflang et al. 2015, p. 41 for a discussion on applications of this functional form in scholarly marketing research)³.

4.1. Defining Adstock

³ This specification also outperforms a lin-lin functional form model that we included as robustness check.

Effects of advertising actions are most often not limited to the period in which the advertising was done, but carry over to subsequent periods (e.g. Leone 1995; Vakratsas and Ambler 1999). Limiting the analysis of advertising effects to only same-period advertising would consequently ignore this dynamic aspect. We could capture these lagged effects by adding additional lagged advertising terms to the model we specify below. This, however, would easily restrain the number of degrees of freedom. We therefore not analyze the advertising series and its lags as such. Instead, we follow common practice in advertising effectiveness research, and analyze the effects of advertising through a parsimonious metric called *adstock* (*adstock*), the cumulative discounted advertising expenditures (e.g. Broadbent 1979, 1984; Ephron and McDonald 2002). The basic idea behind this measure is the fact that by means of advertising, a firm builds up a goodwill stock in the customers' mindset. When no new advertising is added, this stock will gradually deplete over time. When new advertising is added, it will be replenished. We specify *adstock* in the following way (see e.g. Hanssens et al. 2001):

$$(1) \quad adstock_t = (1 - \lambda) \times adv_t + \lambda \times adstock_{t-1},$$

where the first part of the right hand side represents the build-up of *adstock*, and the second part the gradual decay as the carry-over parameter λ is smaller than 1. Building on previous research, we set this parameter for our monthly observations equal to the meta-analytic value of .775 as reported by Leone (1995)⁴.

4.2. Determining Stationarity

Before specifying any time series model, a crucial step is determining whether the included time series are stationary or show a unit root (e.g., Dekimpe and Hanssens 1999). To assess the stationarity of the series, we analyzed the series with the Kwiatkowski-Phillips-Schmidt-Shin (1992) test. Results show that we cannot reject the null hypothesis of stationarity at even the 10% level for both the pass-dist and ticket-dist series, as well as for the *adstock* and gasoline price series. For the customer satisfaction series,

⁴ The data available are prohibitive to reliably estimate a specific carry-over parameter for this firm. However, the robustness checks reported below show that our substantive findings do not depend on the size of the parameter.

however, we reject the null hypothesis at the 5% level, and conclude that this series is evolving. Based on these results, we include the pass-dist, ticket-dist, adstock and gasoline price series in levels, and the customer satisfaction series in first differences. Retailer promotions and own promotions are specified as dummy variables, equaling one when such action was present during that month, zero otherwise.

4.3. Model Specification

Vector-Autoregressive (VAR) models provide us with flexible tools to address the following model challenges: The model should accommodate dynamic effects of firm-initiated marketing actions on the two travel variables (pass-dist and ticket-dist); it should allow for carry-over and spill-over effects of these two variables, and feedback effects through customer satisfaction; finally, it should control for seasonal effects and possible trending behavior.

We model the carry-over, spill-over and feedback effects by treating pass-dist, ticket-dist and satisfaction as endogenous variables. As such, these variables are explained by their own past and the past of the other endogenous variables. Firm-initiated marketing actions, i.e. adstock, retailer promotions and own promotions, in turn, are specified as exogenous variables. The transport provider decides on its advertising and promotion agenda before the start of the year. As such, these actions are not affected on a monthly basis by performance in terms of cumulative distance travelled or customer satisfaction in the previous periods, and could therefore be considered exogenous. Formal Granger Causality tests, allowing for up to 9 lags, confirmed this exogeneity. Hence, while conceptually arguments for the endogeneity of these decisions – setting advertising and promotional budgets with certain demand in mind – could be made, the data refute this⁵. Finally, through the carry-over and spill-over effects, the full effect of one-time firm-initiated marketing actions on the travel and satisfaction variables will go beyond the immediate effects.

⁵ We also estimate a rival model which allows for endogenous firm-initiated marketing actions. Results of this model, which are presented in the model diagnostics section, are inferior to the ones of the focal model, adding to the evidence in favor of the exogeneity of the firm-initiated marketing actions in our model

Public transport usage is a typical seasonal product, with different evolutions for commuting and leisure traveling. Whereas commuting will be lower during the summer season, leisure traveling is then likely to reach its peak. Seasonality hence follows relatively regular cyclical patterns over the year. We can control for these seasonal influences on the endogenous variables in a parsimonious way by including a sinus and cosinus function. We thus specify the following variables:

$$(2) \quad \sinseas_t = \sin\left(\frac{t}{12} \times 2\pi\right)$$

$$(3) \quad cosseas_t = \cos\left(\frac{t}{12} \times 2\pi\right)$$

Instead of estimating 11 monthly or 3 quarterly parameters, we thus only estimate 2 parameters. Finally, we add a deterministic trend to the equations to control for possible up- or downward trends and include the gasoline price to account for the change in costs of the car as a transport alternative. The resulting VARX (Vector AutoRegressive model with Exogenous variables) is specified as:

$$(4) \quad \begin{bmatrix} \lnPassdist_t \\ \lnTicketdist_t \\ \Delta Satis_t \end{bmatrix} = A + \sum_{i=1}^l B_i \times \begin{bmatrix} \lnPassdist_{t-i} \\ \lnTicketdist_{t-i} \\ \Delta Satis_{t-i} \end{bmatrix} + \Gamma \times \begin{bmatrix} \lnAdstock_t \\ RetProm_t \\ OwnProm_t \end{bmatrix} \\ + \Omega \times \begin{bmatrix} gasoline_t \\ trend_t \\ \sinseas_t \\ cosseas_t \end{bmatrix} + \begin{bmatrix} e_{Pk,t} \\ e_{Tk,t} \\ e_{S,t} \end{bmatrix}$$

where

A = vector of intercepts

B_i = matrix of feedback and contagion coefficients at lag i

Γ = vector of advertising and promotion effect coefficients

Ω = vector of control variable coefficients.

The error terms follow a multivariate normal distribution with variance-covariance matrix Σ .

VAR models, when specified properly, can be estimated using simple OLS per equation (see e.g. Greene 2003, p. 588). A downside of VAR models is the fact that they easily suffer from

overparameterization with each included lag adding multiple parameters to be estimated, a burden which becomes larger the more endogenous variables included. Determining the optimal lag order is consequently an essential step. We therefore allowed for up to 3 lags (1 quarter of a year) of the endogenous variables in our model, and determined the lag order based on the BIC of the full model. The optimal BIC was reached for a model containing 1 lag of the endogenous variables⁶. As dynamic effects of advertising are captured by the carry-over structure implied in the adstock specification, and as promotions are known to have very limited lagged effects (especially given monthly data), we do not explicitly include any lagged marketing variables in the model. Our final model thus contains 3 endogenous variables, and 11 variables (including the intercept) in total for each equation. This parsimonious specification allows us to save degrees of freedom⁷. While the observations-to-parameters ratio is on the small side, real issues should be reflected in the basic OLS estimates⁸. These results, however, already show a high number of significant effects, with effect sizes in line with the outcomes of the simulation presented below.

4.4. Model Estimation Procedure

Starting from the basic OLS estimates of the model, we adopt a Monte Carlo simulation approach as introduced by Mark (1990) and used by e.g. Dekimpe and Hanssens (1999). In a first step, we carry out the basic estimation and estimate our VARX model using OLS per equation, which provides us with $\hat{\Sigma}$, the estimated residual variance-covariance matrix. The uncertainty associated with the estimation that may be induced by a low observations-to-parameters ratio is to a large extent reflected in this matrix.

Subsequently, we sample from the multivariate normal distribution $N(0, \hat{\Sigma})$. In a third step, we use these sampled residuals together with the initial (observed) startup values of the different endogenous variables and the estimated parameters from the three equations to create new, ‘simulated’, pass-dist, ticket-dist and

⁶ This number of lags is typical in VAR applications in the existing marketing literature, see for example Pauwels, Aksehirli, and Lackman (2016), Srinivasan, Rutz, and Pauwels (2015) and Wiesel, Pauwels, and Arts (2011).

⁷ We specified as threshold of at least 10 degrees of freedom. The final model has 17 degrees of freedom.

⁸ Results of this first step estimation are provided in Appendix A.

satisfaction series. The worse our original model performs, the larger the variance-covariance of the residuals, and consequently the more the new series will deviate from the original ones. We then use these ‘simulated’ series as input, and re-estimate the model. We repeat this procedure 100,000 times. For each of the 100,000 iterations, we obtain a new estimate of the parameters. This Monte Carlo approach thus provides us with distributions of the parameter estimates, and the less well our model performs, the more this distribution will be spread and the less likely that the parameters will be significant. As such, this approach shows resemblance to a bootstrap approach on cross-sectional data and is a valid alternative/equivalent for bootstrapping in a time-series setting with limited observations. In a final step, we report the median values across all 100,000 simulations as results and judge the significance of our results by looking at the 90% and 95% confidence intervals. This non-parametric percentile-based approach is a common way of analyzing results in e.g. bootstrap and Bayesian estimation settings. As such, we do not follow e.g. Dekimpe and Hanssens (1999) who apply a parametric approach using p-values and based on means and standard deviations⁹. However, in the robustness checks section, we show that the findings based on both approaches are highly similar.

4.5. Short- And Long-Term Effects

We define short-term effects as the immediate effects of changes in one variable on the three dependent variables. Short-term effects of adstock, retailer promotions and own promotions can be derived directly from the model, as they are the parameter estimates obtained from the model for these variables. Short-term feedback effects, however, are derived from the residual variance-covariance matrix Σ of the three equations, building on the multivariate-normality of the residual vector. Following e.g. Dekimpe and Hanssens (1999) and Nijs et al. (2001), we specify the short-term effects as the outcome of a one-unit shock to the residuals of the different equations. We thereby adopt the generalized, simultaneous-shocking approach as proposed by Evans and Wells (1983) and Dekimpe and Hanssens (1999), among

⁹ This approach is also in line with recent calls to move away from p-value based approaches (as implemented by e.g. Dekimpe and Hanssens 1999) towards the reporting of (percentile) confidence intervals.

others. We thus do *not impose* a temporal (causal) ordering between the different endogenous variables, but *allow* for immediate effects. More specifically, the feedback effect of satisfaction on pass-dist corresponds to $\sigma_{S,Pd}/\sigma_{S,S}$, and the feedback effect of satisfaction on ticket-dist is given by $\sigma_{S,Td}/\sigma_{S,S}$, with $\sigma_{i,j}$ the corresponding elements in the residual error variance-covariance matrix Σ . Significance of these effects is judged by looking at the 90% and 95% confidence intervals resulting from the Monte Carlo simulation introduced above.

Besides offering insights on immediate short-term effects, VARX models also allow for the tracking of the over-time impact of changes (shocks) by means of impulse-response functions. Such impulse-response functions consist of two forecasts of the dependent variable (in our case, the focus will be on pass-dist and ticket-dist), the first based on an information set without the shock, the second based on an information set that includes this shock. The difference between the two forecasts indicates the incremental effect of the shock to the dependent variable. We calculate the shocked series by extending the approach for the short-term effects introduced above. Instead of only looking at the immediate impact of the shocks, we track their impact over time. This over-time impact of shocks is based on the dynamics of the model and the lagged effects of the endogenous variables. We apply the same Monte Carlo simulation approach to judge the significance of the effects, using 90% and 95% confidence intervals (see e.g., Villanueva, Yoo, and Hanssens 2008, who use significance levels of .05 and .10). This approach is considerably stricter than the usual 1 standard deviation confidence interval used in most other studies (e.g. Nijs et al. 2001; Pauwels et al. 2004; Steenkamp et al. 2005). As such, long-term findings can be considered conservative.

As the pass-dist and ticket-dist series, the series of focal interest, are both stationary, no persistent effects exist. As a consequence, IRFs will ultimately converge to zero. To judge the long-term effects, we therefore look at the cumulative effect of the shocks over the first 12 months after the shock, as expressed by the sum of the individual IRF coefficients during this period (see e.g. Villanueva, Yoo, and Hanssens 2008). This cumulative interpretation of the long-term effect, in addition, shows strong resemblance with the interpretation of the long-term effects in error-correction models with stationary series (e.g. Van

Heerde et al. 2013; Gijsenberg 2014). As with the short-term effects, long-term effects can be interpreted as elasticities (e.g. Nijs et al. 2001; Pauwels et al 2004; Steenkamp et al. 2005).

5. RESULTS

5.1. Model Diagnostics

Before presenting the results of the model, we first provide insights on model fit. We discuss full sample diagnostics for our focal model and two alternative models. The first alternative model does not allow for lagged effects of advertising through an adstock specification, but only looks at same-period advertising. The second alternative model treats the advertising and promotion actions as endogenous, and allows for one lag of these variables.¹⁰ We evaluate these models based on their AIC, BIC and mean absolute percentage error (MAPE). Diagnostics are based on the median parameter outcomes from the Monte Carlo simulation. In our discussion, we focus on the statistics for the pass-dist and ticket-dist equations, the focal outcome measures of this study. The fit statistics are shown in Table 1.

-- Insert Table 1 about here --

Not accounting for lagged effects of advertising clearly hampers the quality of the model, as both AIC and BIC of the first alternative model deteriorate compared to the focal model (AIC = -4.988 and -7.144 vs -5.175 and -7.186; BIC = -4.465 and -6.621 vs -4.651 and -6.663 for the pass-dist and ticket-dist equations, respectively). The MAPE deteriorates (increases) as well (.234% and .076% vs .220% and .075%). Allowing for endogenous advertising and promotion decisions, in turn, does not add value to the model. AIC, BIC and MAPE deteriorate even further (AIC = -4.611 and -6.588 vs -5.175 and -7.186; BIC

¹⁰ The time span of the dataset is prohibitive to providing out-of-sample predictive fit statistics. It also limits the inclusion of direct lags due to inflation of the number of parameters to be estimated. However, as argued above, one lag is typical in VAR applications in the existing marketing literature, hence the impact of this limitation is likely minor. To fit the two promotion decisions in the VAR setting, both equations are based on a linear probability model instead of a logistic model.

= -4.087 and -6.065 vs -4.651 and -6.663; MAPE = .285% and .104% for the pass-dist and ticket-dist equations, respectively).

Figure 4 and 5 show the full sample forecasts of our focal model and the two alternative models for the (log-transformed) pass-dist and ticket-dist, respectively. These figures confirm that treating the advertising and promotion decisions as exogenous, thereby accounting for lagged effects of advertising through the adstock specification provides superior model performance.

-- Insert Figure 4 about here --

-- Insert Figure 5 about here --

5.2. Substantive Insights

Table 2 presents the estimation results of the focal model. For each of the equations, we report the median values for the different parameters, as well as the 90% and 95% confidence intervals. Median values are indicated in italic when zero is not included in the 90% confidence interval, and indicated in bold and italic when zero is not included in the 95% confidence interval.

-- Insert Table 2 about here --

Insights on the short- and long-term effects of firm-initiated marketing actions on public transport usage and on possible feedback effects through satisfaction based on the model results in Table 2 are presented in Table 3. Similar to Table 2, median values are indicated in italic when zero is not included in the 90% confidence interval, and indicated in bold and italic when zero is not included in the 95% confidence interval.

-- Insert Table 3 about here --

5.2.1. Firm-initiated marketing effects on transport usage

Advertising has a positive immediate effect on pass-dist (median = .074). Interestingly, the elasticity value is nearly 40% smaller than the earlier reported meta-analytic average advertising elasticity value of .12 (Sethuraman, Tellis, and Briesch 2011), but considerably stronger than recently reported values of short-term advertising elasticities of fast-moving consumer goods (e.g. Ataman, van Heerde, and Mela 2010; Van Heerde et al. 2013; Gijsenberg 2014). While immediate effects are relatively strong,

long-term effects are considerably weaker (median = .034) as a consequence of a post-advertising dip. For ticket-dist, no significant short-term effects were found. Long-term cumulative effects, however, are significant, with an elasticity of .013. Retailer promotions, aimed at occasional and mostly leisure oriented traveling, show significant short-term (median = .033) and long-term (median = .028) ticket-dist elasticities, showing these actions' success in attracting additional occasional travelers. As could be expected, no significant effects were found on pass-dist. Own promotions, covering both pass-dist and ticket-dist actions, are successful in increasing both types of travel. Own promotion effects on pass-dist are the strongest of all marketing action effects, with elasticities equaling .202 (short run) and .121 (long run), while elasticities for ticket-dist reach values of .062 (short run) and .043 (long run). These results show that firm-initiated marketing actions can indeed be useful in lifting (temporarily) the usage of public transport for both leisure and commuting goals. Both retailer- and own promotion elasticities are, however, much weaker than generally reported.

5.2.2. Feedback effects on public transport usage

Satisfaction with the service does not have immediate effects on any of the two types of travel. However, it does have a marginally significant negative effect on pass-dist: a positive change in satisfaction decreases the number of pass-dist. As the pass-dist series does not have a unit root, these negative effects are transient and do not persist over time.

5.3. Firm-Initiated Marketing Actions and Satisfaction

In previous section, we reported the negative long-term effect of satisfaction on pass-dist. Analysis of the drivers of satisfaction sheds light on what may be behind this effect. Whereas own promotions have a positive effect on the number of pass-dist, they significantly lower satisfaction, with a short-term elasticity of -.013 and a long-term elasticity of -.011 (zero not included in the 95% confidence interval). Similarly, the cosine component, reaching high values during winter months, low values during summer months, has a positive effect on the number of pass-dist (most commuting is done during winter,

least during summer months with holidays) but a negative on satisfaction. More important, as the satisfaction series is not stationary, these effects are not transient, but persist over time.

The negative effects on satisfaction are likely driven by three factors. First, increased commuting usage of public transport during peaks lowers satisfaction as commuters are, on a daily basis, confronted with more crowded trains. Comfort of traveling can then be reduced, as seating availability diminishes (Verhoef, Heijnsbroek, and Bosma 2017). Due to the fact that capacity is rather fixed, the firm studied cannot use more trains to decrease the crowdedness in the trains. Second, during peaks, the transport provider is catering to a broader range of customers, with the additional commuters likely showing a lower satisfaction a priori (e.g., Keiningham et al. 2014). Finally, during winter times, the firm suffers regularly from serious drops in its operational service performance level. Such crises have been shown to have strong and enduring negative consequences for customer satisfaction (Gijsenberg, van Heerde, and Verhoef 2015). This reasoning is also in line with findings by Mouwen (2015) of positive effects of vehicle tidiness, ease of boarding, seating capacity (all under pressure during peaks) and on-time performance and travel speed (both under pressure during winter times) on travellers' satisfaction. Hence, the negative effect of increases in satisfaction on number of pass-dist should be interpreted in the opposite direction. Decreases in satisfaction happen during periods in which commuting usage of public transport is at its peak. As such, both the firm and the commuters face an infernal feedback loop, with higher usage associated with lower satisfaction, but as commuters often have no real alternatives (e.g. no cycling during winter, roads not being cleared), still higher usage.

5.4. Robustness Checks

We executed multiple robustness checks to assess the stability of our results. Table 4 summarizes the substantive results of these models¹¹.

¹¹ This table does not report feedback elasticities. Reasons for this are twofold: First, significant effects were rare, and if existing, only (except for one) at the 90% confidence level, hence only weakly significant. Second, outcomes of the models with alternative mindset metrics cannot be compared with / interpreted in the same way as the focal model using satisfaction as mindset metric. More detailed results are provided in Appendix B.

-- Insert Table 4 about here --

First, following previous literature, we have fixed the carry-over parameter to the meta-analytic value of .775 (Leone 1995). We therefore performed a sensitivity analysis by allowing this parameter to vary from .500 to .950 with steps of .050. While effect sizes of advertising actions somewhat changed – as could be expected – substantive insights from these models were very similar, and effect sizes of promotional actions were hardly affected. In addition, explanatory power of these models was (at best) as good as that of the focal model, with an average R^2 of .686 across the three equations.

Second, in our focal model, we did not account for price effects given limited variation in price. However, as prices can be changed at the beginning of each year, we include year dummies to account for potential price effects. We thereby had to exclude the trend variable due to severe multicollinearity with these year dummies. Results indicate that here as well, substantive insights are similar. Effect sizes of promotions somewhat changed, but the relative effects – stronger effects for own promotions compared to retailer promotions, and for own promotions on pass-dist compared to ticket-dist – remain. This model, in addition, shows slightly lower explanatory power than our focal model, with an average R^2 across the three equations of .675 compared to .686 for our focal model.

Third, our focal model includes satisfaction as customer feedback metric, which can be considered a mindset metric. However, one could argue that we should also test for other mindset metrics that could ultimately affect people's transport choice. We therefore replaced satisfaction by a) top-of-mind awareness (the extent to which the service offered by this public transport firm was the first option a person would think of with regard to a specific travel goal, averaged over a set of travel goals), b) aided awareness (the extent to which a person recognizes the public transport firm from a list of transport options), and c) the extent to which the firm is considered a reliable choice for traveling. In all cases, substantive insights on the effectiveness of advertising and promotional actions as tools to increase the use of public transport were similar. However, both explanatory power and fit were worse for these models

with regard to the pass-km and ticket-km equations¹²: average R^2 across the two equations of .704, .710 and .703 compared to .752 for our focal model, and average MAPE across the two equations of .156%, .155% and .156% compared to .147% for the focal model. As such, these measures miss out on the relevant actual experience aspect included in the satisfaction measure, that clearly provides valuable information.

Fourth, we estimated our model without the log-transformation of the variables. As a consequence, effects are no longer interpretable as elasticities, and possible diminishing returns to for example advertising are no longer accounted for. Here as well, substantive insights, also with regard to the relative effectiveness patterns of the different firm-initiated marketing actions on the different outcome measures, were very similar. However, explanatory power and model fit worsened: average R^2 across the three equations of .543 compared to .686 for our focal model, and average MAPE across the pass-km and ticket-km equations of 3.296% compared to .147% for the focal model.

Fifth, our dataset, while unique in its nature as times series data are scarce in these industries, is relatively limited in its number of observations. To judge the extent to which our findings could be affected by the time span of our dataset, we re-estimated the model on a series of reduced datasets. We therefore left out up to 3 observations (10% of the data). We applied each of these reductions twice, once by leaving out the last observation(s) in the series, once by leaving out the first observation(s). Overall, substantive insights were in line with the focal model, and results deviate more when we leave out more observations. Across the different models, on average, 54% of the estimates do not have 0 in their 95% confidence interval, which is comparable to the 58% of the focal model.

As a final robustness check, we investigated the extent to which our findings could be affected by using a non-parametric percentile-based approach to judge the significance of the results instead of the more traditional econometric approach using means and standard deviations (e.g. Dekimpe and Hanssens

¹² Given a) that the dependent variables from these two equations constitute the core focal variables of this study, and b) that the dependent variable of the third equation changes in each model, we only compare the results of these models for the pass-km and ticket-km equations.

1999). We therefore calculated the means and standard deviations of the estimated short- and long-term effects, and judged their significance by means of a standard t-test, using significance levels of 5% and 10%. Findings of both approaches are in line with each other, both with regard to the effect sizes and with regard to the significance of the effects.

Based on these results, we can conclude that, overall, our substantive model results seem robust to different model specifications and significance testing approaches.

6. DISCUSSION

6.1. Discussion and Conclusions

All over the world, governments are confronted with negative consequences of car usage for individual transport such as congestion and environmental pollution. To mitigate these problems, policies are developed to foster the usage of public transport. This is mostly done by huge investments in order to simultaneously increase the offering and improve the service level. Among the other tools that can be used to seduce citizens into using public transport instead of their cars are firm-initiated marketing actions like advertising and promotions, two types of actions that have largely been neglected when it comes to evaluating their effectiveness in promoting the usage of public transport. This study fills this gap in the literature, and thus provides useful insights for both policy makers and public transport firms alike.

We show that firm-initiated marketing actions merit the consideration of policy makers and transport firm managers in their effort to attract additional travelers. Both advertising and promotional actions have a positive immediate impact on public transport usage. Especially promotions offered by the firm to its traveler base, using a mix of leisure- and work-oriented special offers, appear effective. Purely leisure-oriented promotions, offered in cooperation with retailers, only affect leisure-related ad-hoc traveling, and resort little to no effect on regular and repeated traveling with month/year passes. Although

effects are not persistent over time, cumulative effects within the first year are significant and considerable, although the initial increase in transport usage is partly offset by a subsequent fallback.

Given that we find positive effects of advertising and promotions, firm-initiated marketing actions can play a role in creating primary demand for public transport. For pass-based traveling, the found advertising elasticity is considerably smaller than the previously reported brand-level elasticities of advertising (Sethuraman, Tellis, and Briesch 2011). This is in line with our expectations of a weaker and perhaps even null effect. However, this short-term advertising elasticity is still much stronger than those reported in recent studies on fast-moving consumer goods (e.g. Ataman, van Heerde, and Mela 2010; Van Heerde et al. 2013; Gijsenberg 2014). It could of course be that the considered firm has relatively strong persuasive advertising tactics. Another explanation though, is that advertising can still be used in this market to create awareness for the advantages of train traveling among unserved customer segments, inducing a relatively strong effect of advertising. The effects of promotions are, however, much weaker than usually reported in the marketing literature. This is in line with research suggesting that promotions mainly have an effect on brand sales and less on category sales (e.g., Bell, Chiang, and Padmanabhan 1999; Nijs et al. 2001).

Whereas the usage of firm-initiated marketing actions has clear positive effects, the relation between travelers' satisfaction and the usage of public transport is somewhat more difficult. Additional investments to improve the service offering and its quality have been shown to increase travelers' satisfaction (Gijsenberg, van Heerde, and Verhoef 2015; Mouwen 2015; Verhoef, Heijnsbroek, and Bosma 2017). This increased satisfaction, however, does not lead to additional usage of public transport for ad-hoc traveling. Periods with increased regular pass-based traveling, on the other hand, are associated with lower satisfaction. Peak periods of public transport usage are usually concentrated in winter times, when other modes of transport like bicycles or cars are less attractive due to e.g. weather conditions. High demand is then associated with many people sharing too limited space inside the trains, which reduces satisfaction (Mouwen 2015). In addition, during these winter times, public transport often faces difficulties due to the weather as well. Such difficulties will further reduce travelers' satisfaction.

(Mouwen 2015). Investments in increasing service quality by providing more space to travelers and a more reliable service thus seems warranted to increase satisfaction in the longer run, even if it does not immediately result in additional usage of public transport.

In a broader sense, one could question the role of satisfaction in public transport and specifically the idea that satisfaction should be a key-performance indicator in many contracts governments have with public transport firms. Our results clearly show that the link between satisfaction and public transport sales is not obvious. Perhaps this also occurs because public transport is a rather monopolistic market. Recent research suggests that even in such monopolistic markets satisfaction can be important for firms though not to increase sales. Satisfaction reduces the costs to serve customers, as for example customers complain less and more inclined to pay their bills (lower bad debt) (Bhattacharya, Morgan, and Rego 2016). Moreover, as a large part of the population uses public transport, a well-organized public transport system with a high quality and thus satisfied users may contribute to more consumer well-being. However, even after additional investments in service quality improvement, increased satisfaction is not guaranteed. The broader the part of the population that is using a service, the more difficult it becomes to reach high levels of satisfaction, as a) it becomes harder to meet the more diverse desires and b) it is likely that the marginal inflow in customers is likely having only have chosen the offer as a choice of last resort, hence having a priori lower levels of satisfaction (e.g. Keiningham et al. 2014).

This study is the first to show the opportunities offered by firm-initiated marketing actions like advertising and promotion in the fostering of public transport usage. We hope that it paves the way for more work in this area.

6.2. Limitations And Future Research

This research suffers from several limitations. We only considered a single European railway firm in a specific geographic market with its' specific market characteristics. Future research might replicate our study in other markets and for other public transport modes. The size of our data set, although large in relative terms as time series data are difficult to collect in these industries, is still small in absolute terms.

We were able to estimate a VAR model on the data, but more data points would have been preferable.

This would also have allowed us to study longer-term indirect effects of service experience via customer satisfaction and referral behavior on service usage (see e.g., Hogreve et al. 2017). In terms of our included firm-initiated marketing actions, we did not study price effects. These effects are somewhat captured by the promotional variables, as these typically comprise temporarily price reductions. Prices are, however, changed on a yearly basis and fixed during the year, implying insufficient over-time variation to study price effects. We executed a robustness check with year dummies, showing no changes in effects. Similar to price also capacity did not change much, while also the offered service in terms of the train schedule remained rather similar. Given the time-period studied and the fact that we have data on the total distance traveled over multiple connections it also not possible to include travel time for other modes of travel. Future research should strive to study longer time periods, as this would also allow for more variation in price (multiple year changes) and capacity. Unfortunately, we do not have these data at our disposal. While we also performed robustness checks on a set of other mindset metrics than satisfaction, we did not have good other attitude measures covering consideration and liking with sufficient variation at our disposal (Hanssens et al. 2014). Finally, we studied the usage of public transport during the Great Recession. Extending the research to economic upbeat times would definitely add to our insights, as several studies have shown that effects of both traditional marketing mix actions and customer satisfaction on purchase behavior are different across economic conditions (e.g. Kumar et al. 2014; Van Heerde et al. 2013)

Despite these limitations, this is probably the first study investigating marketing effects on public transport sales. Our study provides some interesting findings and with a further increase in data availability in multiple industries more of these studies are likely to be possible.

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TABLES

Table 1. Full Sample Diagnostics for Pass-dist and Ticket-dist

| | Pass-dist | Ticket-dist |
|--|-----------|-------------|
| Focal model | | |
| AIC | -5.175 | -7.186 |
| BIC | -4.651 | -6.663 |
| MAPE | .220% | .075% |
| No adstock, exogenous advertising and promotions | | |
| AIC | -4.988 | -7.144 |
| BIC | -4.465 | -6.621 |
| MAPE | .234% | .076% |
| No adstock, endogenous advertising and promotions | | |
| AIC | -4.611 | -6.588 |
| BIC | -4.087 | -6.065 |
| MAPE | .285% | .104% |

Table 2. Model Results

| | 2.5 th pctl | 5 th pctl | Median | 95 th pctl | 97.5 th pctl |
|---|------------------------|----------------------|----------------------|-----------------------|-------------------------|
| Pass-dist equation $R^2 = .659$ | | | | | |
| Constant | 41.451 | 43.963 | <i>56.273</i> | 68.424 | 70.946 |
| lnPassdist _{t-1} | -.865 | -.830 | <i>-.646</i> | -.434 | -.387 |
| lnTicketdist _{t-1} | -1.936 | -1.818 | <i>-1.239</i> | -.648 | -.524 |
| Δ Satis _{t-1} | -8.060 | -7.450 | <i>-4.653</i> | -1.865 | -1.287 |
| lnAdstock _t | .020 | .028 | <i>.074</i> | .120 | .129 |
| RetProm _t | -.055 | -.044 | .013 | .069 | .080 |
| OwnProm _t | .126 | .138 | <i>.202</i> | .267 | .280 |
| gasoline _t | -.194 | -.164 | -.017 | .131 | .161 |
| trend _t | .002 | .003 | <i>.006</i> | .009 | .009 |
| sinseas _t | .006 | .014 | <i>.052</i> | .093 | .101 |
| cosseas _t | .071 | .077 | <i>.112</i> | .148 | .155 |
| Ticket-dist equation $R^2 = .846$ | | | | | |
| Constant | 17.144 | 18.036 | <i>22.618</i> | 26.908 | 27.730 |
| lnPassdist _{t-1} | -.006 | .011 | .086 | .162 | .179 |
| lnTicketdist _{t-1} | -.451 | -.412 | -.209 | .002 | .044 |
| Δ Satis _{t-1} | .593 | .803 | <i>1.837</i> | 2.843 | 3.049 |
| lnAdstock _t | -.008 | -.005 | .012 | .029 | .033 |
| RetProm _t | .009 | .013 | <i>.033</i> | .054 | .058 |
| OwnProm _t | .033 | .038 | <i>.062</i> | .086 | .090 |
| gasoline _t | -.036 | -.026 | .029 | .084 | .095 |
| trend _t | .002 | .002 | <i>.003</i> | .004 | .005 |
| sinseas _t | -.043 | -.040 | <i>-.025</i> | -.011 | -.009 |
| cosseas _t | .001 | .004 | <i>.017</i> | .030 | .033 |
| Satisfaction equation $R^2 = .553$ | | | | | |
| Constant | .103 | .346 | <i>1.520</i> | 2.659 | 2.879 |
| lnPassdist _{t-1} | -.006 | -.002 | .018 | .038 | .043 |
| lnTicketdist _{t-1} | -.155 | -.145 | <i>-.092</i> | -.036 | -.024 |
| Δ Satis _{t-1} | -.690 | -.644 | <i>-.403</i> | -.147 | -.093 |
| lnAdstock _t | -.004 | -.003 | .001 | .006 | .007 |
| RetProm _t | -.003 | -.002 | .004 | .009 | .010 |
| OwnProm _t | -.020 | -.019 | <i>-.013</i> | -.007 | -.006 |
| gasoline _t | -.019 | -.016 | -.002 | .013 | .016 |
| trend _t | -.0005 | -.0004 | -.0001 | .0001 | .0002 |
| sinseas _t | -.006 | -.006 | -.002 | .002 | .003 |
| cosseas _t | -.011 | -.010 | <i>-.007</i> | -.004 | -.003 |

Medians are indicated in italic when 0 is not included in the 90% confidence interval.
Medians are indicated in bold and italic when 0 is not included in the 95% confidence interval.

Table 3. Short- and Long-Term Effects

| | | 2.5 th pctl | 5 th pctl | Median | 95 th pctl | 97.5 th pctl |
|---|------------|------------------------|----------------------|--------------------|-----------------------|-------------------------|
| Advertising Elasticity | | | | | | |
| Pass-dist | Short-term | .020 | .028 | <i>.074</i> | .120 | .129 |
| | Long-term | -.002 | .004 | <i>.034</i> | .064 | .070 |
| Ticket-dist | Short-term | -.008 | -.005 | .012 | .029 | .033 |
| | Long-term | -.001 | .001 | <i>.013</i> | .025 | .027 |
| Retailer Promotion Elasticity | | | | | | |
| Pass-dist | Short-term | -.055 | -.044 | .013 | .069 | .080 |
| | Long-term | -.063 | -.055 | -.015 | .023 | .030 |
| Ticket-dist | Short-term | .009 | .013 | <i>.033</i> | .054 | .058 |
| | Long-term | .010 | .013 | <i>.028</i> | .043 | .046 |
| Own Promotion Elasticity | | | | | | |
| Pass-dist | Short-term | .126 | .138 | <i>.202</i> | .267 | .280 |
| | Long-term | .064 | .074 | <i>.121</i> | .168 | .178 |
| Ticket-dist | Short-term | .033 | .038 | <i>.062</i> | .086 | .090 |
| | Long-term | .022 | .025 | <i>.043</i> | .062 | .066 |
| Feedback (Satisfaction) Elasticity | | | | | | |
| Pass-dist | Short-term | -6.990 | -6.063 | -1.666 | 2.687 | 3.597 |
| | Long-term | -6.891 | -6.250 | -3.204 | -.232 | .381 |
| Ticket-dist | Short-term | -2.246 | -1.907 | -.303 | 1.312 | 1.657 |
| | Long-term | -1.042 | -.778 | .484 | 1.773 | 2.062 |

Medians are indicated in italic when 0 is not included in the 90% confidence interval.

Medians are indicated in bold and italic when 0 is not included in the 95% confidence interval.

Table 4. Significance of effects in robustness check models

| | Advertising | | | | Retailer Promotion | | | | Own Promotion | | | |
|--------------------------|-------------|-----------|-------------|----------|--------------------|-----------|-------------|-----------|---------------|-----------|-------------|-----------|
| | Pass-Dist | | Ticket-Dist | | Pass-Dist | | Ticket-Dist | | Pass-Dist | | Ticket-Dist | |
| | ST | LT | ST | LT | ST | LT | ST | LT | ST | LT | ST | LT |
| Focal model | X | x | - | x | - | - | X | X | X | X | X | X |
| Carry-over: .500 | X | x | - | - | - | - | X | X | X | X | X | X |
| Carry-over: .550 | X | x | - | - | - | - | X | X | X | X | X | X |
| Carry-over: .600 | X | X | - | - | - | - | X | X | X | X | X | X |
| Carry-over: .650 | X | x | - | - | - | - | X | X | X | X | X | X |
| Carry-over: .700 | X | x | - | - | - | - | X | X | X | X | X | X |
| Carry-over: .750 | X | x | - | x | - | - | X | X | X | X | X | X |
| Carry-over: .800 | X | x | - | x | - | - | X | X | X | X | X | X |
| Carry-over: .850 | X | x | - | X | - | - | X | X | X | X | X | X |
| Carry-over: .900 | X | - | - | X | - | - | X | X | X | X | X | X |
| Carry-over: .950 | X | - | - | X | - | - | X | X | X | X | X | X |
| Year dummies | X | x | - | - | - | - | X | X | X | X | X | X |
| Top-of-mind awareness | X | X | - | - | - | - | X | X | X | X | X | X |
| Aided awareness | X | X | - | X | - | - | X | X | X | X | X | X |
| Reliable choice | X | X | - | X | - | - | X | X | X | X | X | X |
| Non-log model | X | X | - | - | - | - | X | X | X | X | X | X |
| Last observation out | X | - | - | - | - | - | X | X | X | X | X | X |
| First observation out | X | x | - | - | - | - | X | X | X | X | X | X |
| Last 2 observations out | X | - | - | - | - | - | X | X | X | X | X | X |
| First 2 observations out | X | - | - | X | - | - | - | - | X | X | X | X |
| Last 3 observations out | x | - | - | - | - | - | X | X | X | X | X | X |
| First 3 observations out | X | - | - | X | - | - | - | - | X | X | X | X |
| Mean & Stdev based | ** | ** | <i>ns</i> | * | <i>ns</i> | <i>ns</i> | ** | ** | ** | ** | ** | ** |

X: 0 is not included in the 95% confidence interval. x: 0 is not included in the 90% confidence interval.

-: 0 is included in the 90% confidence interval.

******: $p < .05$; *: $p < .10$; *ns*: $p > .10$

FIGURES

Figure 1. Conceptual Framework

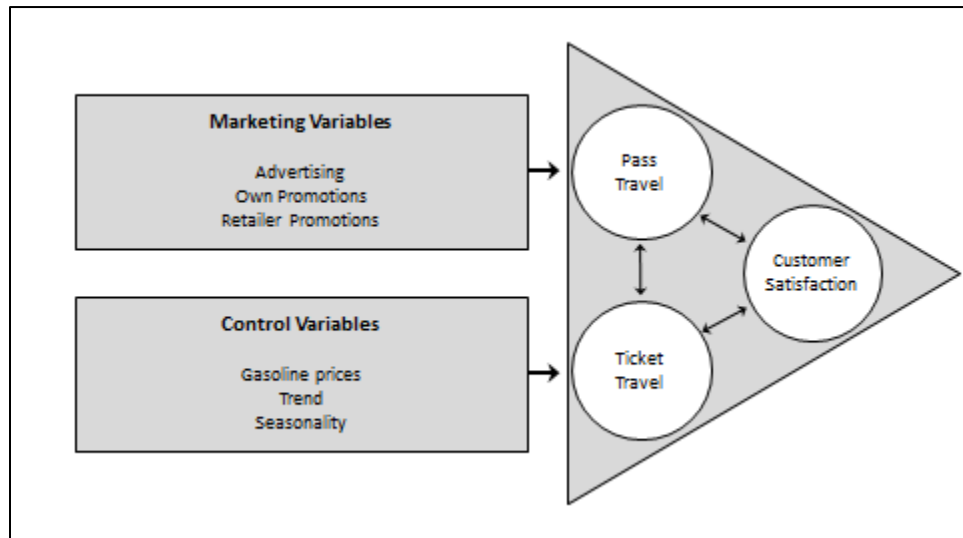


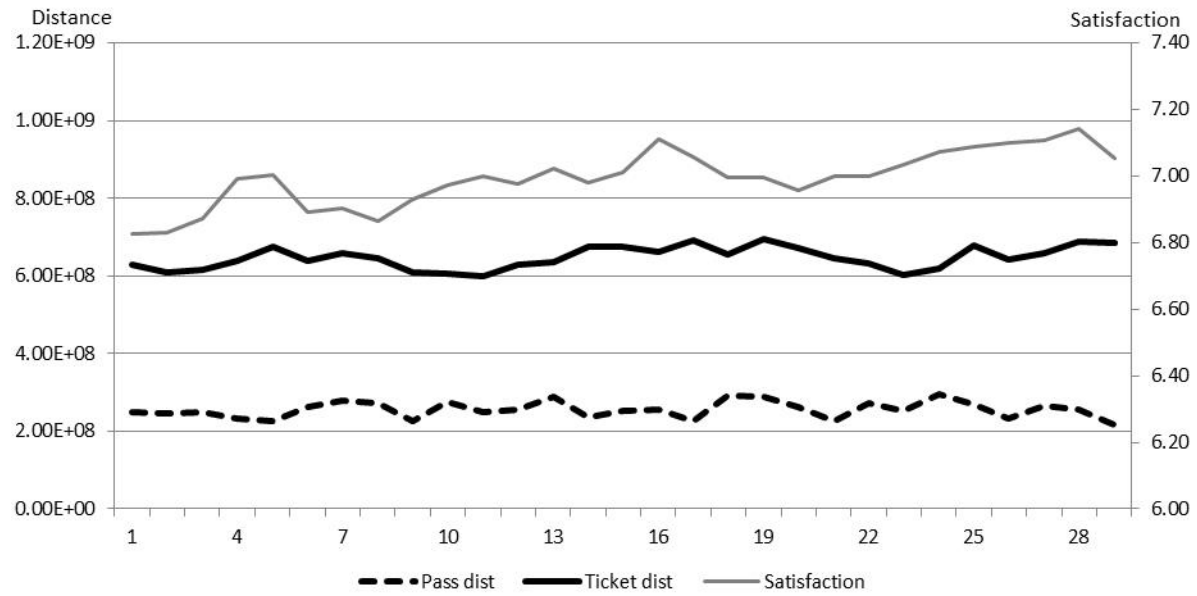
Figure 2. Public Transport Usage and Customer Satisfaction Evolution

Figure 3. Public Transport Usage and Firm-Initiated Marketing Actions

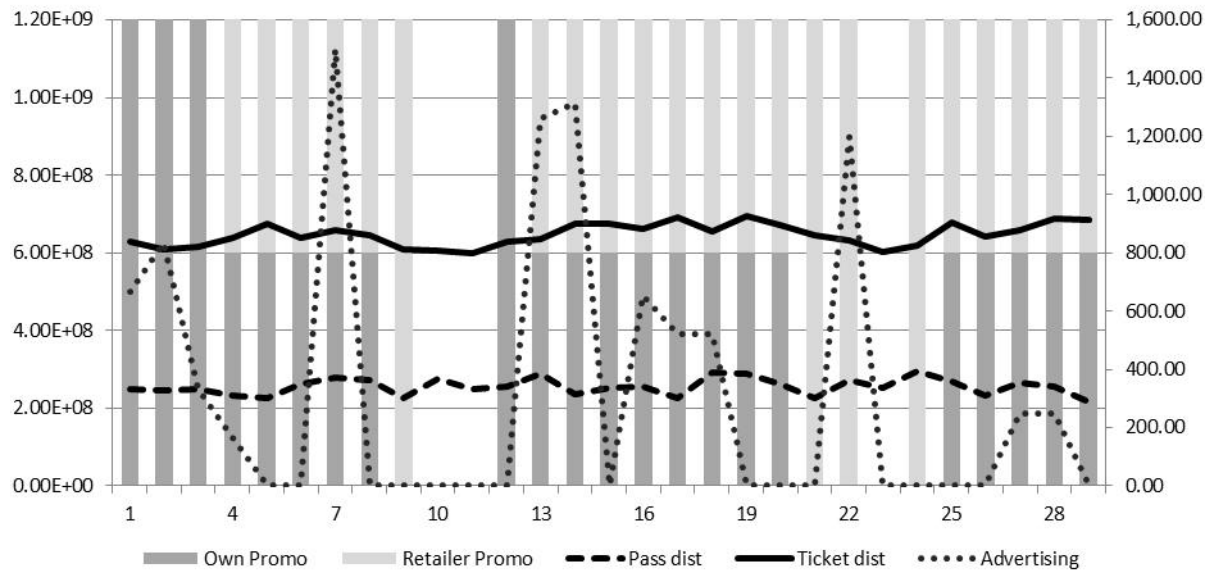


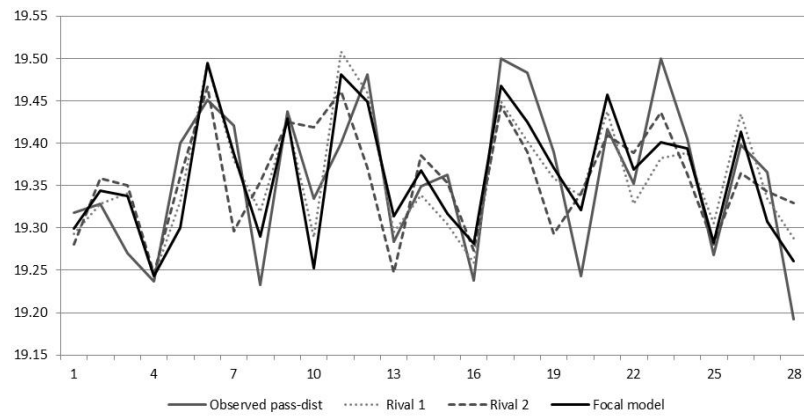
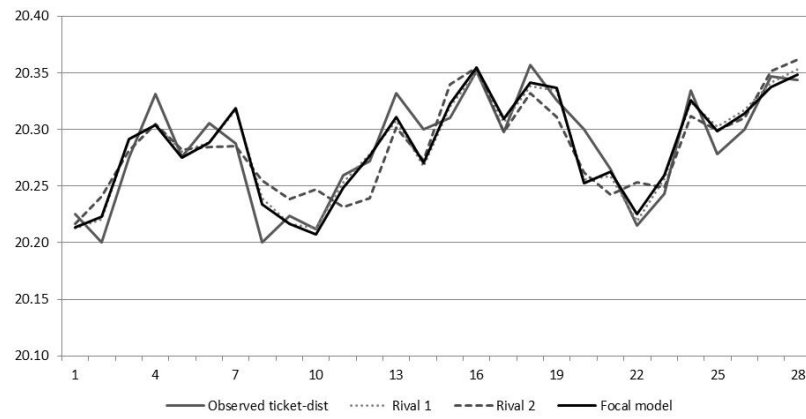
Figure 4. Full-Sample Predictive Performance for Pass-dist

Figure 5. Full-Sample Predictive Performance for Ticket-dist

APPENDIX A. ORIGINAL OLS MODEL RESULTS

Table A1. Original OLS Model Results

| | Estimate | St.dev. | T-stat | P-value (2-sid) |
|------------------------------|-----------------------------|---------|--------|-----------------|
| Pass-dist equation | R² = .661 | | | |
| Constant | <i>55.531</i> | 9.747 | 5.697 | 0.000 |
| lnPassdist _{t-1} | <i>-0.595</i> | 0.184 | -3.233 | 0.005 |
| lnTicketdist _{t-1} | <i>-1.245</i> | 0.427 | -2.913 | 0.010 |
| ΔSatis _{t-1} | <i>-4.555</i> | 2.059 | -2.212 | 0.041 |
| lnAdstock _t | <i>0.072</i> | 0.035 | 2.070 | 0.054 |
| RetProm _t | 0.013 | 0.042 | 0.298 | 0.769 |
| OwnProm _t | <i>0.199</i> | 0.055 | 3.640 | 0.002 |
| gasoline _t | -0.014 | 0.112 | -0.127 | 0.900 |
| trend _t | 0.050 | 0.029 | 1.685 | 0.110 |
| sinseas _t | <i>0.111</i> | 0.030 | 3.662 | 0.002 |
| cosseas _t | <i>0.006</i> | 0.002 | 2.458 | 0.025 |
| Ticket-dist equation | R² = .847 | | | |
| Constant | <i>21.763</i> | 3.561 | 6.112 | 0.000 |
| lnPassdist _{t-1} | 0.077 | 0.067 | 1.145 | 0.268 |
| lnTicketdist _{t-1} | -0.158 | 0.156 | -1.014 | 0.325 |
| ΔSatis _{t-1} | <i>1.758</i> | 0.752 | 2.336 | 0.032 |
| lnAdstock _t | 0.012 | 0.013 | 0.924 | 0.368 |
| RetProm _t | <i>0.033</i> | 0.015 | 2.117 | 0.049 |
| OwnProm _t | <i>0.061</i> | 0.020 | 3.065 | 0.007 |
| gasoline _t | 0.028 | 0.041 | 0.687 | 0.501 |
| trend _t | <i>-0.023</i> | 0.011 | -2.177 | 0.044 |
| sinseas _t | 0.016 | 0.011 | 1.493 | 0.154 |
| cosseas _t | <i>0.003</i> | 0.001 | 3.710 | 0.002 |
| Satisfaction equation | R² = .557 | | | |
| Constant | 1.384 | 0.932 | 1.485 | 0.156 |
| lnPassdist _{t-1} | 0.017 | 0.018 | 0.947 | 0.357 |
| lnTicketdist _{t-1} | -0.084 | 0.041 | -2.052 | 0.056 |
| ΔSatis _{t-1} | -0.322 | 0.197 | -1.633 | 0.121 |
| lnAdstock _t | 0.001 | 0.003 | 0.371 | 0.715 |
| RetProm _t | 0.004 | 0.004 | 0.969 | 0.346 |
| OwnProm _t | <i>-0.013</i> | 0.005 | -2.474 | 0.024 |
| gasoline _t | -0.002 | 0.011 | -0.149 | 0.883 |
| trend _t | -0.002 | 0.003 | -0.589 | 0.564 |
| sinseas _t | <i>-0.007</i> | 0.003 | -2.342 | 0.032 |
| cosseas _t | 0.000 | 0.000 | -0.670 | 0.512 |

Estimates are indicated in italic when $p < .10$.
Estimates are indicated in bold and italic when $p < .05$.

APPENDIX B. ROBUSTNESS CHECK RESULTS

Table B1. Short- and Long-Term Effects in Robustness Check Models: Percentile Method

| | Advertising | | | | Retailer Promotion | | | | Own Promotion | | | |
|--------------------------|-------------|-------------|-------------|-------------|--------------------|-------|---------------|---------------|---------------|---------------|---------------|---------------|
| | Pass-Dist | | Ticket-Dist | | Pass-Dist | | Ticket-Dist | | Pass-Dist | | Ticket-Dist | |
| | ST | LT | ST | LT | ST | LT | ST | LT | ST | LT | ST | LT |
| Focal model | <i>.074</i> | <i>.034</i> | .012 | <i>.013</i> | .013 | -.015 | <i>.033</i> | <i>.028</i> | <i>.202</i> | <i>.121</i> | <i>.062</i> | <i>.043</i> |
| Carry-over: .500 | <i>.029</i> | <i>.015</i> | .003 | .004 | .018 | -.013 | <i>.036</i> | <i>.030</i> | <i>.202</i> | <i>.124</i> | <i>.060</i> | <i>.044</i> |
| Carry-over: .550 | <i>.035</i> | <i>.018</i> | .004 | .004 | .017 | -.014 | <i>.035</i> | <i>.030</i> | <i>.202</i> | <i>.123</i> | <i>.060</i> | <i>.044</i> |
| Carry-over: .600 | <i>.041</i> | <i>.021</i> | .005 | .006 | .016 | -.014 | <i>.035</i> | <i>.029</i> | <i>.203</i> | <i>.123</i> | <i>.061</i> | <i>.044</i> |
| Carry-over: .650 | <i>.048</i> | <i>.024</i> | .006 | .007 | .015 | -.015 | <i>.035</i> | <i>.029</i> | <i>.204</i> | <i>.122</i> | <i>.061</i> | <i>.044</i> |
| Carry-over: .700 | <i>.057</i> | <i>.027</i> | .008 | .009 | .014 | -.015 | <i>.034</i> | <i>.028</i> | <i>.204</i> | <i>.122</i> | <i>.062</i> | <i>.044</i> |
| Carry-over: .750 | <i>.068</i> | <i>.031</i> | .011 | <i>.012</i> | .013 | -.015 | <i>.034</i> | <i>.028</i> | <i>.203</i> | <i>.121</i> | <i>.062</i> | <i>.044</i> |
| Carry-over: .800 | <i>.081</i> | <i>.037</i> | .014 | <i>.015</i> | .012 | -.015 | <i>.033</i> | <i>.028</i> | <i>.202</i> | <i>.120</i> | <i>.062</i> | <i>.043</i> |
| Carry-over: .850 | <i>.096</i> | <i>.042</i> | .018 | <i>.019</i> | .011 | -.015 | <i>.033</i> | <i>.027</i> | <i>.200</i> | <i>.120</i> | <i>.062</i> | <i>.043</i> |
| Carry-over: .900 | <i>.117</i> | .050 | .023 | <i>.024</i> | .011 | -.015 | <i>.032</i> | <i>.027</i> | <i>.197</i> | <i>.119</i> | <i>.062</i> | <i>.043</i> |
| Carry-over: .950 | <i>.142</i> | .057 | .031 | <i>.033</i> | .011 | -.014 | <i>.032</i> | <i>.026</i> | <i>.195</i> | <i>.118</i> | <i>.061</i> | <i>.042</i> |
| Year dummies | <i>.071</i> | <i>.038</i> | .005 | .008 | .025 | -.012 | <i>.041</i> | <i>.033</i> | <i>.163</i> | <i>.110</i> | <i>.046</i> | <i>.039</i> |
| Top-of-mind awareness | <i>.098</i> | <i>.051</i> | .010 | .010 | .016 | -.004 | <i>.032</i> | <i>.027</i> | <i>.188</i> | <i>.087</i> | <i>.046</i> | <i>.041</i> |
| Aided awareness | <i>.092</i> | <i>.046</i> | .009 | <i>.013</i> | .023 | -.014 | <i>.024</i> | <i>.026</i> | <i>.176</i> | <i>.082</i> | <i>.054</i> | <i>.045</i> |
| Reliable choice | <i>.095</i> | <i>.042</i> | .008 | <i>.012</i> | .020 | .014 | <i>.030</i> | <i>.019</i> | <i>.190</i> | <i>.089</i> | <i>.046</i> | <i>.042</i> |
| Non-log model | <i>.074</i> | <i>.039</i> | .018 | .023 | 6.434 | -.370 | <i>18.128</i> | <i>14.140</i> | <i>46.842</i> | <i>21.462</i> | <i>27.768</i> | <i>26.182</i> |
| Last observation out | <i>.057</i> | .028 | .011 | .011 | .003 | -.018 | <i>.033</i> | <i>.026</i> | <i>.193</i> | <i>.119</i> | <i>.061</i> | <i>.043</i> |
| First observation out | <i>.071</i> | .033 | .011 | .012 | .019 | -.013 | <i>.037</i> | <i>.029</i> | <i>.201</i> | <i>.120</i> | <i>.061</i> | <i>.042</i> |
| Last 2 observations out | <i>.063</i> | .031 | .013 | .012 | .007 | -.016 | <i>.034</i> | <i>.028</i> | <i>.200</i> | <i>.120</i> | <i>.063</i> | <i>.044</i> |
| First 2 observations out | <i>.073</i> | .030 | .016 | <i>.016</i> | .016 | -.007 | .021 | .018 | <i>.201</i> | <i>.118</i> | <i>.060</i> | <i>.045</i> |
| Last 3 observations out | <i>.058</i> | .029 | .010 | .009 | .006 | -.016 | <i>.034</i> | <i>.027</i> | <i>.199</i> | <i>.119</i> | <i>.063</i> | <i>.043</i> |
| First 3 observations out | <i>.079</i> | .031 | .018 | <i>.017</i> | .015 | -.010 | .021 | .017 | <i>.191</i> | <i>.109</i> | <i>.056</i> | <i>.041</i> |
| Average values | .062 | .029 | .013 | .012 | .013 | -.012 | .030 | .025 | .196 | .117 | .061 | .043 |

Medians are indicated in italic when 0 is not included in the 90% confidence interval.

Medians are indicated in bold and italic when 0 is not included in the 95% confidence interval.

Table B2. Short- and Long-Term Effects in Robustness Check Models: Means and Standard Deviations Method

| | Advertising | | | | Retailer Promotion | | | | Own Promotion | | | |
|--------------------|-------------|-------------|-------------|-------------|--------------------|-------|-------------|-------------|---------------|-------------|-------------|-------------|
| | Pass-Dist | | Ticket-Dist | | Pass-Dist | | Ticket-Dist | | Pass-Dist | | Ticket-Dist | |
| | ST | LT | ST | LT | ST | LT | ST | LT | ST | LT | ST | LT |
| Focal values | .074 | .034 | .012 | .013 | .013 | -.015 | .033 | .028 | .202 | .121 | .062 | .043 |
| Mean value | .074 | .034 | .012 | .013 | .013 | -.016 | .033 | .028 | .203 | .121 | .062 | .044 |
| Standard deviation | .028 | .010 | .018 | .007 | .035 | .024 | .013 | .009 | .039 | .029 | .015 | .011 |
| T-statistic | 2.644 | 3.273 | .654 | 1.799 | .364 | -.654 | 2.641 | 2.964 | 5.158 | 4.178 | 4.241 | 3.868 |
| P-value (2-sided) | .017 | .004 | .522 | .090 | .721 | .522 | .017 | .009 | .000 | .001 | .001 | .001 |

Table B3. Diagnostics for Robustness Check Models

| | R² | | | | MAPE¹³ | | |
|--------------------------|----------------------|-------------|---------|-------------|--------------------------|-------------|---------------|
| | Pass-dist | Ticket-dist | Mindset | Average | Pass-dist | Ticket-dist | Average |
| Focal model | .659 | .846 | .553 | .686 | .220% | .075% | .147% |
| Carry-over: .500 | .647 | .840 | .549 | .679 | .217% | .075% | .146% |
| Carry-over: .550 | .651 | .841 | .550 | .680 | .217% | .074% | .146% |
| Carry-over: .600 | .654 | .842 | .550 | .682 | .217% | .075% | .146% |
| Carry-over: .650 | .657 | .842 | .551 | .684 | .217% | .075% | .146% |
| Carry-over: .700 | .659 | .844 | .551 | .685 | .218% | .075% | .146% |
| Carry-over: .750 | .660 | .845 | .552 | .685 | .219% | .075% | .147% |
| Carry-over: .800 | .658 | .846 | .553 | .686 | .221% | .075% | .148% |
| Carry-over: .850 | .655 | .847 | .555 | .686 | .223% | .075% | .149% |
| Carry-over: .900 | .648 | .848 | .556 | .684 | .225% | .075% | .150% |
| Carry-over: .950 | .640 | .849 | .558 | .682 | .228% | .075% | .152% |
| Year dummies | .640 | .895 | .491 | .675 | .232% | .059% | .145% |
| Top-of-mind awareness | .559 | .849 | .371 | .593 | .240% | .073% | .156% |
| Aided awareness | .559 | .861 | .839 | .753 | .240% | .070% | .155% |
| Reliable choice | .548 | .842 | .579 | .656 | .248% | .071% | .159% |
| Non-log model | .506 | .838 | .284 | .543 | 5.096% | 1.495% | 3.296% |
| Last observation out | .647 | .836 | .529 | .671 | .211% | .077% | .144% |
| First observation out | .661 | .838 | .553 | .684 | .219% | .075% | .147% |
| Last 2 observations out | .653 | .825 | .526 | .668 | .210% | .077% | .144% |
| First 2 observations out | .659 | .831 | .544 | .678 | .228% | .073% | .151% |
| Last 3 observations out | .655 | .828 | .528 | .670 | .215% | .078% | .147% |
| First 3 observations out | .692 | .847 | .494 | .678 | .223% | .066% | .145% |

¹³ As the dependent variable series in the mindset metric equations mostly consisted of first differences due to non-stationarity of the variables, in all but one model also of log-transformed variables, these series are characterized by both many values near zero and considerable fluctuations. We therefore follow the recommendations by Armstrong (2001, p.277) and do not rely on relative error measures expressed in percentages like the MAPE, and hence average the fit across the pass-distance and ticket-distance equations which also form the core focus of this study.

VITAE

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